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**Developing A Novel Continual Learning Strategy To Address The Forgetting Problem For AI Models In Human-In-The-Loop Procedures**

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**Abstract:**
*__Purpose:__ Devising an effective strategy to tackle the forgetting problem in AI models that continually learn from newly annotated classes (e.g., organs and tumors) while preserving the knowledge of previously learned classes.
*__Methods and Materials:__ We leveraged 14 publicly available datasets to train an AI model, each dataset comprising various partially annotated anatomical structures. AI predictions associated with the highest uncertainty were identified and delegated to radiologists for review. A selective group of 12 subjects was chosen from a total of 200, and two radiologists independently revised the AI predictions of four specific organs (namely, aorta, postcava, stomach, and gallbladder) in each selected subject. Primarily, we implemented continual learning strategies during the fine-tuning process. In this context, the pre-trained model was fine-tuned with all revised cases, encapsulating both AI-predicted and human-revised labels. We compared two experimental settings: "Revision-Focused Continual Learning," which involved fine-tuning solely with revised labels from 12 cases, and "All Data Continual Learning," which incorporated fine-tuning with all 200 cases. Additionally, the Multilayer Perceptron (MLP) in our AI model was modified to create organ-based MLP layers, allowing for specific MLP layer updates that corresponded to the revised organs.
*__Results:__ The continual learning strategy proved most successful among various data manipulation methods, leading to improvements in the average dice score of human revised labels (from 81.0%±7.7% to 83.8%±5.8%) while preserving minimal performance degradation in AI predicted labels (90.8%±5.2% to 91.2%±4.9%). The "Revision-Focused Continual Learning" approach resulted in a significant decline in the average dice score of unrevised labels (by 10.4%), while the "All Data Continual Learning" method avoided the forgetting problem but demonstrated limited efficiency in enhancing the average dice score of revised labels (an increase of merely 0.8%).
*__Conclusions:__ Incorporating "Revision-Focused" methods during fine-tuning of a pre-trained model can lead to the forgetting problem. Conversely, our novel continual learning strategy effectively mitigates this issue by maintaining the model's original capabilities while assimilating the benefits of newly revised annotations.
*__Clinical Relevance/Application:__ Our proposed fine-tuning strategy enhances diagnostic accuracy and minimizes annotation efforts, thus facilitating long-term learning and promoting trust in the model's decision-making process. This approach fosters continual improvement and the integration of the latest medical knowledge, thereby increasing the model's value in evidence-based healthcare settings.

**Category (Complete)**: Theranostics - Latest trends and advances
**Questions (Complete)**:
- **Disclosure of "Off-Label" usage**: No, I do not intend to discuss off-label uses
- **IRB / IACUC Response**: Human subject, and received IRB approval
- **Has this work been previously presented or published?**: No
- **Trainee Research Prize**: Not Applicable
- **I verify** : True

**Attached Files:** QUANTITATIVE AND QUALITATIVE RESULTS OF VARIOUS CONTINUAL LEARNING STRATEGIES. (PDF, 414968 bytes)

**Status:** Complete